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TECHNICAL MEMORANDUM

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SPECKLE REDUCTION IN SYNTHETIC APERTURE RADAR IMAGES

D.M. McDONALD

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SPECKLE REDUCTION IN SYNTHETIC APERTURE RADAR IMAGES

D.M. McDonald

S U M M A R Y

This survey reviews noise reduction techniques of particular relevance to the multiplicative speckle noise associated with synthetic aperture radar images. Where appropriate, mention is made of the Generalised Synthetic Aperture Radar (GSAR) software package developed by MacDonald Dettwiler and Associates for the processing of raw SAR data in a standard format into image data.

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1. INTRODUCTION

Synthetic Aperture Radar (SAR) has been developed in recent years to improve the along-track resolution of sidelooking airborne radar. Spaceborne platforms such as Seasat (1978) and the shuttle-borne radars (SIR-A and SIR-B) have allowed the monitoring of large areas of the earth's surface for remote sensing and other purposes. Spaceborne SAR has proven to be complementary to optical and infrared imaging systems such as Landsat; the radar system is active with oblique illumination across the swath, whereas Landsat is passive with a constant sun elevation across the image, varying with the season. Thus only the radar can operate day and night and at any latitude. Radar wavelengths can penetrate clouds, allowing imaging of normally cloud-covered regions.

Ease of interpretation of radar and optical images varies with the application; for example the oblique illumination of SAR enhances faults, fractures and lineaments (depending on the look direction), whereas streams and details of vegetation tend to show up better in Landsat images. In SAR ocean studies, internal waves are detectable through their modulation of surface waves, with the potential benefits of enhancing our understanding of oceanic processes and extracting bathymetric information.

Because of the coherent nature of the SAR imaging process, detected images suffer from the presence of multiplicative noise or speckle, analogous to that observed with lasers. This speckle contamination confuses the interpretation and classification of SAR images and has stimulated much research into techniques of speckle reduction. Unlike Landsat multiband images, SAR images to date have been singleband, although multiband sensors are planned (eg SIR-C). Classification of radar images together with images recorded at different times, or with different sensors such as Landsat have been attempted.

The problems of segmentation and object detection are closely related to classification. Some approaches have specifically aimed at identifying geometrical structures such as edges and corners. The review however will concentrate on those techniques directed at improving the visual interpretability of SAR images.

2. SPECKLE

2.1 Introduction

The standard model for the image restoration problem is that the original intensity distribution f is acted on by a linear system with point spread function h to produce a blurred image b. The recording process involves a (possibly non linear) transformation S and introduces additive noise n' (usually assumed to be white and Gaussian).

Thus the intensity of the observed image g is given by

$$g = S(f*h) + n'$$

Many techniques are available for restoring images contaminated by such additive noise.

The first important characteristic of a radar speckle model, is that the original intensity distribution f is corrupted by multiplicative noise n due to the coherent nature of the imaging process.

This corrupted distribution takes the place of f above, and is acted on by recording system with point spread function h. If there is negligible additive noise and the system is linear, then

$$g = (f.n)*h.$$

This formula, with or without the point spread function, is the basis of most of the specific speckle noise reduction techniques. The point spread function leads to spatial correlation between adjacent pixels. This is of particular significance when the final image is oversampled, for example to match standard map scales.

The second important feature of the radar speckle problem is simply the magnitude of the variance of the multiplicative noise; a mean of 1 with a variance equal to the mean squared for a single look intensity image. Improvements in interpretability can be made by manipulating the look up table (LUT) on display, (ie the table relating pixel value to displayed brightness) which changes the effective variance, for example by implementing a square root function (Matthews et al 1984), or a high pass filter (Lim and Nawab, 1981). The combination of poor SNR and the multiplicative nature of the noise leads to particular problems in edge detection and classification. In the presence of speckle, the required spatial frequency bandwidth to recognise even a binary object must be several times the spatial frequency bandwidth of the object itself (Arsenault and April, 1986).

The terminology of image processing has been strongly influenced by photographic recording. It is convenient to refer to images as being either amplitude or intensity (amplitude squared) images. Some care must be taken in interpreting the literature as to which is being referred in any context. Note that the GSAR package produces an amplitude image as its standard product.

2.2 Speckle models

Porcello et al (1976) modelled a typical radar scene as "a collection of specular scatterers superimposed upon a background of diffuse scattering surfaces". The diffuse scatterers form the speckle background and the highly coherent microwave transmitter serves as a source analogous to a laser in a laser-illuminated optical system.

Goodman (1976) studied the speckle observed in laser systems in some detail. He viewed speckle in statistical terms as a random-walk phenomenon. He considered monochromatic, polarised radiation u, viz

$$u(x,y,z,t) = A(x,y,z)\exp(i2\pi\nu t)$$

where ν is frequency and $A(x,y,z)$ is a complex phasor amplitude

ie $$A(x,y,z) = |A(x,y,z)|\exp\{i\theta(x,y,z)\}$$

The observable is the irradiance at (x,y,z), given by

$$I(x,y,z) = \lim_{T\to\infty}\frac{1}{T}\int|u(x,y,z;t)|^2dt = |A(x,y,z)|^2$$

To derive the probability distribution of the intensity, an analogy was made with the classical random-walk problem.

The complex amplitude $A(x,y,z)$ is regarded as being made up of contributions from many elementary scattering areas on the rough surface. Thus the phasor amplitude can be represented by

$$A(x,y,z) = \sum_{k=1}^{N} |a_k| \exp(i\phi_k)$$

The two important assumptions which are now made are:

(1) the amplitude a_k and phase ϕ_k of the contributing elementary phasors are independent of each other and of the amplitude and phase of other phasors.

(2) the phases of the elementary contributions are equally likely to lie anywhere in the interval $(-\pi,\pi)$; ie the surface is rough compared with the wavelength.

These two assumptions allow the adoption of the classical random-walk in a plane solution. Provided the number of contributions N is large, then the real and imaginary parts of the complex field at (x,y,z) are *independent zero-mean, identically* distributed Gaussian random variables, ie the speckle can be described as

$$a(x,y) = a_R(x,y) + ia_I(x,y).$$

where a_R and a_I each have variance $\sigma^2{}_a$

The speckle intensity is then

$$I = I(x,y) = a^2{}_R(x,y) + a^2{}_I(x,y)$$

with phase

$$\theta = \tan^{-1} \frac{a_I(x,y)}{a_R(x,y)}$$

The intensity or irradiance I obeys negative exponential statistics, ie its probability density function is of the form

$$P(I) = \frac{1}{\bar{I}} \exp(-I/\bar{I}) \ , \ I \geq 0$$

where

$$\bar{I} = 2\sigma_a^2 \qquad \text{(Guenther et al, 1978)}$$

The standard deviation of this function is equal to $\bar{I}$.

The density function of θ is flat.

Hence the probability that the irradiance exceeds a given threshold I_t is

$$P(I > I_t) = \exp(-I/\bar{I}_t), \quad I_t \geq o$$

Note that the form of this probability density function (corresponding to a single look intensity image) explains the multiplicative nature of speckle noise. In other words, for a uniform scene, the standard deviation of the intensity equals the mean intensity.

If the amplitude (rather than intensity) of the image is considered, then the probability density function becomes a Rayleigh distribution. Small intensity values will be spread out and large values will appear to be compressed (if the result is scaled). The standard deviation (for one look) will be reduced by almost a factor of 2 to 0.5227. Converting from an intensity display to an amplitude display is equivalent to remapping the look up table (LUT) in the display processor as previously mentioned. Extensions of this technique will be discussed later.

The contrast ratio is a convenient measure of the effect of speckle on an image. It is given by

$$\gamma = \frac{\text{standard deviation}}{\text{mean value}}$$

with a value of 1 for a single look intensity image. It is the basic aim of speckle reduction techniques to reduce this ratio, for homogeneous areas.

The approach outlined above considered an array of many scatterers randomly distributed in a cell with dimensions large compared to a wavelength. The central limit theorem leads to a Gaussian probability distribution for the total field arising from the mutual interference from these independent scatterers. Envelope detection leads to a Rayleigh-distributed envelope and a negative exponential intensity distribution. The n th normalised moment of the detected intensity I is given by (Oliver, 1984)

$$I_n = \frac{\langle I^n \rangle}{\langle I \rangle^n} = n$$

If the number of scatterers is reduced, then there appear additional terms in the expressions for the moments. For example, Oliver quotes the second normalised moment of the intensity as being

$$I_2 = 2(1 - \frac{1}{N}) + \frac{\langle a^4 \rangle}{N\langle a^2 \rangle}$$

where N is the number of scatterers and a the scattering amplitude.

Various models have been proposed for the scattering process. They incorporate fluctuations in the number of scatterers or the scatterer cross section. The independent K-distribution, for example, arises from a negative binomial scatterer density distribution, with independent scatterers. Oliver proposed a model using a Γ-lorentzian cross section fluctuation (including periodicity), in which the fluctuation has Γ-distributed statistics and lorentzian spatial-frequency distribution. This model includes the effects of correlation between scatterers and the finite illumination size, and reduces in the appropriate limit to the independent K-distribution model. This work on correlated K-distribution models for representing speckle is continuing (Oliver, 1985).

Ouchi et al (1987) found that the speckle statistics depend on backscatter cross section fluctuations when the correlation scale of the fluctuations is comparable with, or exceeds, the SAR resolution. They found that in addition to the impulse response function corresponding to Gaussian speckle, the autocorrelation function of the speckle included the convolution of the autocorrelation function of the cross-section fluctuations with this impulse response, referred to as non-Gaussian speckle.

3. NOISE REDUCTION TECHNIQUES

Noise reduction techniques will be described briefly, together with the results of practical comparisons. These comparisons tend to be subjective, when applied to actual images; there are advantages in first testing the techniques on simulated images. However, in this case the validity of the underlying models cannot be tested.

3.1 Multilooking

The most commonly used speckle reduction technique is that of multilooking. The principle behind the technique is that the sum of N identically distributed, real-valued, uncorrelated random variables has a mean value which is N times the mean of any one component and a variance which is N times the variance of one component. If we add N uncorrelated speckle patterns on an intensity basis, the contrast ratio of the resultant speckle pattern is reduced by $\sqrt{N}$.

Uncorrelated speckle patterns can be obtained through time, angle, frequency or polarisation diversity. In the GSAR processor, azimuth multilooks are achieved by dividing up the Doppler frequency domain during azimuth compression, with a user-specified maximum overlap of successive looks. Because of the one to one relation between along-azimuth position and Doppler frequency, this is equivalent to dividing up the synthetic aperture length.

Lee (1986) has compared the effects of using amplitude images in multilooking with using intensity images and then taking the square root to obtain amplitude. Lee found a slight advantage, as the number of looks increases, in the second technique. The GSAR package in fact averages in amplitude.

As shown by Porcello et al (1976), the summation of N uncorrelated random variables, each with the identical exponential probability distribution $\frac{1}{\sigma_o} e^{-\mu/\sigma_o}$, has the density function

$$P(\mu) = \frac{1}{(\sigma_o/N)\ (N-1)!}\left(\frac{\mu}{\sigma_o/N}\right)^{N-1} \exp\left(\frac{-\mu}{\sigma_o/N}\right),\ 0 \le \mu \le \infty$$

The ratio of the mean to the standard deviation in this distribution is $N^{\frac{1}{2}}$, as pointed out earlier. On taking the square root, the standard deviation of the amplitude of this speckle noise becomes (Lee, 1986)

$$\sigma_v = \sqrt{\frac{N\Gamma^2(N)}{\Gamma^2(N+\frac{1}{2})} - 1}$$

Note that for a single look, the standard deviation is reduced from 1 to 0.5227, merely by taking the square root. This is almost as effective as using 4 looks in intensity.

There are some limitations with the multilooking techniques. The most obvious is the degradation in resolution: a synthetic aperture reduced in length by a factor of M means the azimuth resolution is degraded by the same factor. Further problems may arise if there are specular reflectors in the image, or other strongly angle-dependent features. Tomiyasu (1983) modelled the speckle in a pixel in terms of isotropic scatterers. He also considered the effect of specular or quasi specular surfaces comparable to pixel dimensions or larger, where the response is highly angle-dependent. Tomiyasu (1984) also considered the effect of just a few dominant scatterers. He found, in this case, some correlation between the spectral response and the sub-pixel texture. Scivier and Orr (1986) have developed an adaptive enhancement technique directed at the situation where scene reflectivity changes during the integration period. Finally, multilooking must be incorporated in the SAR processor. Most of the techniques to be described below are applied to the processed image.

3.2 Image domain filters

Li et al (1983) compared multilooking with several types of image domain filter. In the latter case, single-look, full resolution images are processed. The images are then convolved with a low pass filter window which effectively produces a weighted average of several adjacent pixels. This convolution may be implemented in the frequency domain before final detection (ie on the Fourier Transform of the complex image pixels).

Li et al compared five filters, designed with the same rectangular equivalent widths

$$REW = \int \frac{W(x)}{W(o)}\,dx$$

The filters chosen were

(a) Box filter

$$W(x) = \begin{cases} 1, & -\frac{1}{2} \le x \le \frac{1}{2} \\ 0, & \text{otherwise} \end{cases}$$

(b) Triangle filter

$$W(x) = \begin{cases} 1 - |x|, & -1 \le x \le 1 \\ 0, & \text{otherwise} \end{cases}$$

(c) Sinc squared filter $W(x) = \left(\frac{\sin \pi x}{\pi x}\right)^2$

(d) Exponential filter $W(x) = \exp(-2|x|)$

(e) Lorentzian filter $W(x) = \left(\frac{1}{1 + \pi^2 x^2}\right)$

The test was performed on Seasat scenes and an equivalent number of looks calculated.

$$ENL = \frac{(E[P])^2}{VAR[P]}$$

where P is the pixel intensity.

Improvements were found using this measure, the degree of improvement depending on the scene. Different filters yielded different impulse responses of course, but the question of the impact of these on image interpretability was not addressed.

The main disadvantage of image domain filter techniques lies in the amount of computation required to process to full resolution and to perform the filtering. A further limitation lies in the storage requirements for full resolution images.

Guenther et al (1978) also compared several techniques including multilooks, spatial averaging and square and square root operations, on simulated digital speckle images of a test pattern. The effectiveness was judged by a set of observers on the basis of minimum detectable contrast as a function of object size. They found no change for the two non-linear filters, but however a subjective improvement in noise for the squaring filter. Note that in practice, power law operations for visual presentation can be implemented by modifying the look up table in the display device, and are thus highly efficient.

Smith (1978) presented a noise filtering technique which in principle bears a family relation to the IDF techniques. The algorithm consists in essence of transforming the image, applying a low pass filter and transforming back to the image domain. Smith employed a Hadamard-Walsh transform and an adaptive low pass filter based on Students t-distribution to remove statistically insignificant transform spectra. The technique was demonstrated on photographic images.

3.3 Additive noise reduction

A wide range of linear spatially invariant filters have been used in image processing. However, these have been developed primarily for handling images possibly distorted by a non-linear but spatially invariant process and degraded by additive noise (eg Chin and Yeh, 1983). Such filters include weighted and unweighted block averaging, Gaussian and various edge-detecting filters. The smoothing filters tend to blur edges, and all have problems when applied to radar images degraded by multiplicative noise.

For the simple model in which the observed image comprises an ideal image corrupted by multiplicative noise (ie the point spread function and any system non-linearities may be neglected) then homomorphic filtering may be applied. This technique preprocesses the observed image (in this case by taking the logarithm) so as to transform non-additive noise into additive noise. After applying standard noise reduction techniques, the inverse operation is applied to generate the estimate of the ideal image. However

there are problems when the noise-degraded image is operated on by a point spread function. Deconvolution techniques to remove this effect are available but their performance degrades for noisy images such as typical radar images (Frost et al 1982).

The median filter is particularly effective in removing isolated spot noise, but has also been applied to images corrupted by multiplicative noise. Each pixel is replaced by the median pixel in a block of its neighbours. This non-linear and heuristic filter in practice preserves edges much better than the linear filters. It has been used as a basis of comparison for other algorithms.

Scollar et al (1984) used the local median and the interquartile distance instead of the mean and variance on photographic and other data, for spike removal and edge preservation.

Pratt et al (1985) developed a pseudomedian filter, a computationally efficient approximation to the standard median filter.

Various extensions of the Kalman filter have been applied to images by various authors. These recursive methods deal with additive noise, and include line-by-line recursive filters as well as extensions to two dimensions (eg Woods and Ingle, 1981). These models use a semicausal type of model, in which a pixel value in the original image is a linear combination of previous pixel values plus an adjustment (input) term. The observed image consists of this image corrupted by additive noise. (Nahi and Assefi 1972, Beimond et al 1982, Jain 1977, Chen 1979.) Lee (1981) applied the Kalman filter to a linearised approximation to the multiplicative speckle noise case to derive an adaptive local statistics algorithm, discussed in greater detail later.

A recent publication describes an adaptive block Kalman filter (Azimi-Sadjadi, 1987) which uses an autoregressive image model with an observation model that includes multiplicative noise.

3.4 Wiener filtering

Wiener filters have been applied mainly to the additive noise case. They are based on minimising the mean square error (MMSE filters) between the original and the restored image and require some knowledge of the noise (and true signal) characteristics. Pratt (1972) presented a generalised Wiener filtering technique in which the filter is applied to a transformed version of the data (for example, using the Fourier, Hadamard or Karhunen-Loeve transformations). Some work has however been done on image restoration in the presence of film grain noise.

Walkup and Choens (1974) addressed the problem of additive, signal modulated noise, ie

$$r(x,y) = s(x,y) + cf[s(x,y)].n(x,y)$$

where $r(x,y)$ is the noisy image, $s(x,y)$ is the ideal image, c some constant, f is usually a non linear function, and $n(x,y)$ is a <u>zero</u> <u>mean</u> uncorrelated noise process.

The two dimensional Wiener filter has a spatial frequency domain transfer function of the form

$$W(u,v) = \frac{\phi_{rs}(u,v)}{\phi_{rr}(u,v)}$$

where ϕ_{rr} and ϕ_{ss} are the spectral densities of $r(x,y)$, the observed, degraded image, and $s(x,y)$ the ideal image and ϕ_{rs} represents their cross spectral density. For the model above (with zero mean uncorrelated noise), it turns out that $\phi_{rs} = \phi_{ss}$, and the resulting filter is given by

$$W(u,v) = \frac{\phi_{ss}(u,v)}{\phi_{ss}(u,v) + c^2\, \phi_{s_1 s_1}(u,v) * \phi_{nn}(u,v)}$$

where $\phi_{s_1 s_1}$ represents the spectral density of $s_1(x,y) = f(s(x,y))$ and ϕ_{nn} is the spectral density of the noise process. For white noise and stationary image statistics, this may be written as

$$W(u,v) = \frac{\phi_{ss}(u,v)}{\phi_{ss}(u,v) + c^2 \overline{S_1{}^2} N_o}$$

where $\overline{S_1{}^2}$ is the mean squared value of $s_1(x,y)$.

This filter thus has a higher gain at spatial frequencies where the signal to noise ratio is high than it is where the ratio is low.

Kondo et al (1977) extended the application of the Wiener filter to the case where the image is degraded by a system point spread function h, ie

$$I(x,y) = s(x,y)*h(x,y) + f[s(x,y)*h(x,y)]\bullet n(x,y)$$

$$= s(x,y)*h(x,y) + s_1(x,y)\bullet n(x,y)$$

Their filter is of the form

$$W(u,v) = \frac{\Phi_{ss}(u,v).H^*(u,v)}{\Phi_{ss}(u,v)|H(u,v)|^2 + \Phi_{s_1 s_1}(u,v)*\Phi_{nn}(u,v)}$$

where $H(u,v)$ represents the Fourier Transform of $h(x,y)$. The relation between this filter and that of Walkup and Choens is clear, when $h(x,y)$ is replaced by a δ function. Kondo also considered one form of a multiplicative noise model:

$$I(x,y) = n(x,y)\bullet[s(x,y)*h(x,y)]$$

with a corresponding filter

$$W(u,v) = \frac{\Phi_{ss}(u,v).H^*(u,v)/\bar{n}}{\Phi_{ss}(u,v)|H(u,v)|^2 + \frac{1}{|\bar{n}|^2}\, \Phi_{n_1 n_1}(u,v)*[\Phi_{ss}(u,v)|H(u,v)|^2]}$$

where $n_1(x,y) = n(x,y) - \bar{n}$

Note that this form of a multiplicative model is different from that considered in coherent radar studies by, for example Frost et al, viz $I(x,y) = [s(x,y) \bullet n(x,y] * h(x,y)$. As will be discussed later, Frost's filter is based on a Wiener approach.

The Wiener filtering work described above has been directed specifically to photographic studies, in which the multiplicative noise affects the signal after degradation by the point spread function.

The above forms of filter assume that the image statistics are spatially invariant. This assumption, although justifiable for photographic processes, is not so valid when applied to SAR data. One extension is to assume only local spatial invariance, updating the statistics as the filter scans across the image.

3.5 Adaptive filters

3.5.1 Kansas filter

Frost et al (1981, 1983) considered the equation as discussed previously

$$I(x,y) = [s(x,y) \bullet n(x,y)] * h(x,y)$$

where I is the observed image, s the (desired) image reflectivity, n the multiplicative noise and h the system point spread function. As with the Wiener filter approach, the MMSE filter for stationary image data was calculated by minimising $E[(r(t) - I(t) * m(t))^2]$. This approach leads to the transfer function

$$M(f) = \begin{cases} \left[\dfrac{\bar{n} S_r(f)}{S_r(f) * S_n(f)} \right] \dfrac{1}{H^*(f)} & , f \neq 0 \\ \dfrac{1}{n} & , f = 0 \end{cases}$$

where $n = E\{n(t)\}$ and f is the spatial frequency. Sr(f) and Sn(f) are the power spectral densities of signal and noise respectively. The filter in this form strictly applies to a homogeneous area. At this point, the filter is recognisably of the same family as the (Wiener) filters derived by Kondo et al and Walkup and Choens.

Frost et al now apply a standard model for the terrain reflectivity, r(t), regarding it as an autoregressive process with an autocorrelation $R_r(\tau)$ and two sided power spectral density of the form:

$$R_r(\tau) = \sigma_r^2 e^{-a|\tau|} + \bar{r}^2$$

with

$$S_r(f) = \frac{2\sigma_r^2 a}{a^2 + 4\pi^2 f^2} + \bar{r}^2 \delta(f)$$

where the values of the parameters a, σ_r^2 and r^2 differ for different terrain categories.

The model for the multiplicative white noise is

$$R_n(\tau) = \sigma_n^2 \, \delta(\tau) + \bar{n}^2$$

with

$$S_n(f) = \sigma_n^2 + \bar{n}^2 \, \delta(f)$$

Here σ_n^2 and n^2 are scene independent, but depend on the sensor, and a varies only slowly in a given image and can also be considered constant. Substituting, the impulse response derived is given by

$$M'(t) = K_1 \alpha e^{-\alpha|t|}$$

where α depends on the observed image characteristics $(\sigma_I/\bar{I})^2$. Frost et al derived a direct proportionality of the form $\alpha = K_2(\sigma_I/\bar{I})^2$. K_1 and K_2 are normalising constants.

This filter form reflects the form of the model chosen for the desired (ideal) image and noise. It is extended to cope with non stationary statistics by adaptively varying α. A larger value of α implies a narrower impulse response and less averaging than a smaller value. Thus in a region containing an edge where the variance σ_I^2 is large, α is also large, less averaging will occur and the edge will be better preserved.

The filter is made adaptive by updating the value of $(\sigma_I/\bar{I})^2$ in a moving window across the image.

Frost et al demonstrated the filter on a Seasat image of the Goldstone Array. They concluded the filter smoothed noise better in homogeneous areas and preserved point targets and edges better than the median filter.

Freitag et al (1983) compared the Kansas filter on agricultural scenes with the unweighted median filter, for the 5 x 5 and 11 x 11 cases. Their criteria were edge detection and classification accuracy. There are detail differences between the filter implementation in the Freitag paper and that published by Frost et al. However the principle of narrower filtering where the image is noisy is maintained in order to preserve edges.

Their conclusions, based on classifying agricultural fields, were that the adaptive filter performed better for high contrast edges, but that low contrast edges were blurred by averaging. The size of the selected window depended upon the resolution of the system and the size of the homogeneous elements making up the heterogeneous scene.

Panda (1978) developed an adaptive filter for additive noise which uses a local operator, the 'sample window autocorrelation' to identify

regions which are noisy and do not contain edges. The local operator controls an heuristically selected filter of similar operation to the Kansas filter.

3.5.2 Lee local statistics filter

In Jong-Sen Lee's adaptive approach, the effect of the point spread function is neglected. The observed image is then expressed as

$$I(x,y) = s(x,y)\bullet n(x,y)$$

where n is the multiplicative noise with a negative exponential distribution (when displayed as intensity).

The observed pixel is linearised by the first order Taylor expansion about (I, n), viz

$$I = \bar{n}\bar{s} + \bar{s}(n-\bar{n}) + \bar{n}(s-\bar{s})$$

The filter derived from minimising the mean square error is of the form

$$\hat{s}_{ij} = \bar{s}_{ij} + K_{ij}\,(I_{ij} - \bar{n}_{ij}\,\bar{s}_{ij})$$

where

$$K_{ij} = \frac{\bar{n}_{ij} Q_{ij}}{\bar{s}^2_{ij}\,\sigma_n{}^2 + \bar{n}^2_{ij}\,Q_{ij}}$$

Q_{ij} is the estimated variance of the noise-free image, given by

$$Q_{ij} = \frac{\mathrm{var}(I_{ij}) + \bar{I}_{ij}{}^2}{\sigma_n{}^2 + \bar{n}^2_{ij}} - \bar{s}_{ij}{}^2$$

Lee's filter is made adaptive through estimating the 'local statistics': local values of var(I) and I are estimated from the image (eg a window around the pixel being estimated) and $\sigma_n{}^2$ is estimated either independently (assuming it to be stationary) or by some appropriate algorithm from the image. The filter thus amounts to a linear weighted sum of the local mean and the image itself.

If the linearisation mentioned above is not made, then an extra term occurs in the denominator in the expression for K_{ij}; viz

$$K_{ij} = \frac{\bar{n}_{ij} Q_{ij}}{\bar{s}^2_{ij}\,\sigma_n{}^2 + \bar{n}^2_{ij}\,Q_{ij} + \sigma^2_n\,Q_{ij}}$$

In this form, the filter would be identical to that derived by Kuan et al (1985) for multiplicative noise. The approach of Kuan et al may be regarded as a generalisation of Lee's work, and can be applied to any

model of the form $I = s+n'$, where n' is unbiassed and possibly signal-dependent noise. In the multiplicative case,

$$n' = (n-1) \bullet s$$

and thus fits their model.

The advantage of Lee's filter is that is does not require a model of the original signal. However, artifacts can be produced (Lee, 1983b). A disadvantage lies in the method of estimating the variances. If too small an area is used to estimate the observed image variance, then it may happen that the calculated Qij is sometimes negative. This can be tested and set to zero. In addition, if the noise variance is spatially variant, its estimation may be time consuming. Ideally it is measured from the local variance of a flat or almost flat area.

This algorithm does not smooth in areas where the local variances are large such as near edges. To smooth near edges while preserving sharpness Lee (1981a) extended the algorithm essentially by redefining the neighbourhood for determining the local statistics, according to the local gradient.

If the local variance exceeds a preset threshold, an edge is assumed to be present within the window. The window is divided into a number of possibly overlapping subareas and the local means calculated. A gradient mask is then applied to these means to determine the orientation. The area used to calculate the local mean and variance then includes only those subareas on the centre pixel side of the edge. The increase in computing time is kept within bounds by controlling the threshold above which the extra processing occurs.

Arsenault and Levesque (1984) combined a homomorphic filter with the local statistics algorithm (as applied to additive noise).

Kim and Haralick (1985) compared the extended local statistics filter with weighted median, average and Gaussian filters. The local statistics algorithm is sensitive to the estimated noise variance, and Kim and Haralick adopted a procedure to accommodate the observed spatial variance of the noise of their images. They updated the noise variance at the start of each row of the image. The technique was to obtain, for each row, n local variances (one for each of the n pixels in the row), order them, and average the m smallest. Each local variance is calculated from a neighbourhood around the centre pixel.

The comparison was on the basis of noise removal, contrast stretching, edge enhancement and texture preservation. The adaptive filter using local gradient and local statistics removed noise well without contrast loss or edge blurring, but tended to blur images in homogeneous regions, that is its texture preservation was only 'fair'. The weighted median removed noise but with poorer contrast and edge blurring properties, but was superior in preserving texture.

The Gaussian filter removed noise without contrast loss, but smoothed edges. These three filters all performed better, as expected, than the average filter.

A recent publication describes an adaptive filter, specifically for unity noise variances, based on writing the formula for multiplicative noise as

$$I(x,y) \;=\; s(x,y) + (n(x,y)-1)\bullet s(x,y)$$

The second term represents an unbiassed signal dependent noise term. The filter derived is of the form

$$\hat{s}_{ij} \;=\; \bar{I}_{ij} + \tfrac{1}{2}\left(1 - \frac{\bar{I}_{ij}^{\,2}}{\mathrm{VAR}(I_{ij})}\right)(I_{ij} - \bar{I}_{ij})$$

The filter of this form, using the local statistics calculated over a 5x5 block, was compared with other 5x5 filters, including the median, averaging and Lee's adaptive filter, as well as with multilooking. This filter was considered superior on the basis of resolution broadening and the derived equivalent number of looks. The filter has the advantage of comparative computational simplicity (Nathan and Curlander, 1987). Extending the derivation for arbitrary noise variance yields the extended Lee formula (page 12).

Mastin (1985) applied 5 x 5 filters including the K-nearest neighbour filter of Davis and Rosenfeld (1978) to a synthetic image. More recently, Durand et al (1987) applied ten 7 x 7 filters to a SAR image of cropland; they preferred the extended Lee filter.

Scivier and Orr (1986) adapted Lee's approach to enhance multi-look images, aimed at the case where scene reflectivity changes during the integration period, as with large specular targets (Tomiyasu, 1983). The essence of their technique is to obtain local statistics information (the local mean and variance) from a window comprising a set of centre pixels (one per look) and a set of neighbouring pixels in each look. One look is designated the 'preferred look'. Thus in the equation

$$\hat{s}_{ij} \;=\; \bar{s}_{ij} + K_{ij}(I_{ij} - \bar{I}_{ij}) \qquad \text{(cf p 11)}$$

I_{ij} is the pixel value in the preferred look, and

$\bar{I}_{ij}$ (and $\mathrm{var}(I_{ij})$) are derived from the mn^2 pixels in the nxn window over m looks.

If the variation between looks can be accounted for by speckle then the enhanced image approaches the normal multilook image. If the scene varies significantly between looks, the result approaches the 'preferred' look.

This technique was demonstrated on a Seasat ocean image. The results according to the authors suggested a greater preservation of dynamic features over the standard multilook method, with a similar degree of speckle reduction.

3.5.3 Comparison of adaptive approaches

Frost and Lee both considered a multiplicative noise model, and Frost included the effect of the point spread function as well. Comparing Frost's approach (neglecting the point spread function) directly with Lee's, then similarities and differences are apparent.

Both Frost and Lee developed a filter with stationary characteristics, and then make the filter adaptive by using local image statistics derived from a window about the pixel. However, their development of a stationary filter differs. Frost essentially uses a Wiener filter approach to derive the equation

$$M(u,v) = \frac{\bar{n}\Phi_{ss}(u,v)}{\Phi_{nn} * \Phi_{ss}(u,v)}$$

He then invokes models for the noise-free image and multiplicative noise; the noise free image is modelled by an exponentially decaying autocorrelation function for the signal (plus an offset to account for the average grey level) and the noise is modelled as white uncorrelated noise with non-zero mean. This specific model leads to a particular form of the filter in which, by manipulation, the observed image statistics feature rather than those of the noise-free image. This is an obvious requirement for a practical filter, but the cost lies in the necessity to assume a specific mathematically tractable image formation model; using different models may not necessarily lead to such a convenient final form.

Note that Kondo et al tested their Wiener filter (with a different noise model) by using a real image to which they added the effects of noise and the point spread distribution. Thus the parameters in their Wiener filter equation were known. As would be expected, they found superior performance using the known autocorrelation function of their original distribution compared to assuming it to be white uncorrelated noise. They did not try models such as that used by Frost. Walkup and Choens similarly used simulated images with known parameters.

Lee made no assumptions about the noise free image characteristics. He approximated the expression for pixel intensity in terms of an expansion about the average intensity,

$$I_{ij} = s_{ij}\bar{n}_{ij} + n_{ij}\bar{s}_{ij} - \bar{n}_{ij}\bar{s}_{ij}$$

and applied what can be considered a Kalman filter approach to derive an estimate of the noise-free pixel value. The input s_{ij} is operated on by a linear filter with transfer function n_{ij} and has added to it a zero-mean noise term $s_{ij}(n_{ij}-n_{ij})$ to yield I_{ij}.

The Kalman filter is closely related to the Wiener filter (Sorensen, 1970).

Comparing Lee's approach with Frost's, the final form of the filters derived are totally different. If Frost's model is valid for a particular image, then the use made of this prior knowledge (the assumed autocorrelation function) in principle should lead to 'better' results than a method that doesn't use prior knowledge. The question becomes one of the validity of the selected model.

These two adaptive methods share similar characteristics in that the average and variance in a local area are used, with an estimate, derived in some other step, of the noise.

3.6 Sigma filter

This approach is based on the sigma probability of the Gaussian distribution. The sigma filter selectively averages only those pixels within a given $x\sigma_n$ range in a given $(2n+1)x(2m+1)$ window while excluding significantly different pixels, with a modification to cope with spot noise. If a $2\sigma_n$ range is specified, then for the multiplicative noise case, the pixels used in averaging are those in the range

$$I_{ij} - 2\sigma_n I_{ij} \text{ to } I_{ij} + 2\sigma_n I_{ij}$$

where σ_n is the noise standard deviation. The unweighted average of these pixels replaces the centre pixel.

For a Gaussian distribution, 95.5% of random samples are within the 2σ range. The assumption in this method is that pixels in the window within this range are from the same distribution. Thus, substantial edges will tend not to be blurred.

Isolated spot noise may not be removed by the filter. One solution is to specify a threshold; if the total number of pixels within the range is less than the threshold, it is assumed that the centre pixel is an isolated spot. The pixel is then replaced by a 4-neighbour average. Alternatively, a 3x3 window with threshold=1 can be used in another filter pass.

Note that it is the product of noise standard deviation and a selectable parameter that specifies the range. The choice of this parameter is somewhat subjective; Lee used a $2\sigma_n$ range for most of his published examples, with several passes through the data and with windows from 3x3 to 7x7. Note that for specific images, where details of interest are close in grey level to surrounding pixels, he suggested a small window size with a reduced range (Lee 1983a, 1986).

Lee has also applied a biased Sigma filter, in which pixels in the upper intensity range are averaged separately from those in the lower. The centre pixel is replaced by the closer average. This biased filter enhances contrast and sharpens ramp edges.

The Sigma filter is a relatively efficient technique. Its effectiveness compares favourably with straight averaging and median filters, although a comparison with the local statistics method was inconclusive (Lee 1983a).

Lee (1983b) also compared the performance of the sigma filter with several other filters for the case of additive noise. These included the gradient inverse weighting scheme of Wang et al (1981), found to be inferior in reducing noise variance. This filter computes the absolute differences between the centre pixel and each of its neighbours in a 3 x 3 cell. The centre pixel is replaced by the average of its own value and the value obtained by weighting each neighbour by its inverse absolute difference. Thus values which differ greatly from the centre pixel are weighted less, although other weighting schemes satisfying this principle can be devised. The principle can be adapted to multiplicative noise by modifying the weighting so that pixels with large relative differences are weighted less. A scheme analogous to Wang et al's could replace the absolute difference by a fractional relative difference (less than or equal to one) based on the ratio of the centre pixel to the other pixels (or its reciprocal).

Lee also considered an edge preserving filter (Nagao and Matsuyama (1979)) which considers a 5 x 5 neighbourhood around the centre pixel, and creates nine overlapping subregions, comprising eight directional regions of seven pixels (including the centre pixel) and one 3 x 3 subregion around the centre pixel. The centre pixel is replaced by the mean of the subregion having minimum variance. Lee points out that the sigma-filter average could be used in place of the mean. However, the Nagao filter suffers from shape distortion because of its directional subregions, as well as being more computation-intensive.

3.7 Bayesian techniques

One would expect that prior knowledge about the original image and/or the noise distribution should lead to a better estimate of the original image than methods not using such knowledge. Representative models are available. One significant group of reduction techniques are those classed as Bayesian.

Bayesian methods have been applied mainly to additive noise images (Hunt 1977), but recently Geman and Geman (1984) have developed a technique applicable to the multiplicative noise case as well.

Their technique applies to degraded images described by

$$g = \phi(H(f)) \bullet N$$

where f is the original, g the observed images. H is the point spread function, ϕ a possibly nonlinear transformation, N an independent noise field and $\bullet$ an invertible operation such as addition or multiplication.

If the above equation is viewed as a stochastic problem, then one must estimate the restored image given only the recorded image and some statistical knowledge of the noise. The posterior conditional density is given by Bayes' Law:

$$P(f/g) = \frac{P(g/f)\ P(f)}{P(g)}$$

The MMSE (minimum mean square error) estimates are the mean of the posterior density p(f/g), and MAP (maximum a posterior) estimates are the mode of the distribution. ML (maximum likelihood) estimates correspond to the case where all original estimates are equally likely.

For an mxm image with L grey levels, the number of possible images is L^{m^2}, which rules out any direct search for the optimum restored image.

These techniques tend to require iterative runs to converge on an optimum result.

Habibi (1972) used a partial difference equation to realise a two-dimensional recursive model (a counterpart to the one-dimensional Kalman filter) yielding the MMSE estimate for additive white Gaussian noise.

Burkhardt and Schorb (1982) derived an MAP estimate using the Viterbi algorithm. Naderi and Sawchuk (1978) developed a Bayesian algorithm based on a 'noise cheating algorithm' (Zweig et al 1975), which they showed could be justified on ML grounds.

The technique of Geman and Geman's MAP method is applicable to multiplicative-noise-degraded images. Their noise model is closer to Lee's than to Frost's, in that they do not consider the effect of the point spread function.

Geman and Geman adopted a stochastic model for the original image, representing it as a Markov random field, MRF (equivalent to a Gibbs distribution). Pixel grey levels and the presence and orientation of edges are viewed as analogous to states of atoms or molecules in a lattice-like physical system. The posterior distribution is also an MRF with similar structure for a range of operations including blurring, non-linear deformations and additive and multiplicative noise.

Gradual temperature reduction in the physical system to isolate low energy states ('annealing') corresponds to obtaining the MAP (maximum a posteriori) estimate of the image given the degraded image.

Geman and Geman developed a 'stochastic relaxation' algorithm, which generates a sequence of images that converge to the MAP estimate. The sequence evolves by local changes in pixel grey levels and in the locations and orientations of boundary elements. The stochastic relaxation allows random changes that decrease the posterior distribution as well as changes that increase it. This reduces the problem of local maxima, which can occur with deterministic iterative-improvement methods.

For a neighbourhood around each pixel, a set of cliques is defined with associated potentials. These potentials are defined so that the Gibbs measure is related to the a priori probabilities associated with the uncorrupted image, the noise process and the sensor characteristics. Calculating or measuring the clique structures, probabilities and potentials represent a significant challenge with this approach.

Kuan et al (1987) developed a MAP filter using local statistics (ie a non-stationary mean, non-stationary variance or NMNV model). Their model requires the solution of a cubic equation for each pixel in the image.

3.8 Geometric filter

Crimmins (1985) adopted a radically different approach with his so-called geometric filter. This algorithm considers the gray level profile of an image line as a geometric shape. It is based on applying a single iteration of convex hulling algorithm alternately to the image and its complement. It is essentially a one dimensional algorithm applied in four different directions in the two-dimensional image: horizontal, vertical and the two diagonal directions. The effect of the filter is gradually and iteratively to remove narrow valleys and towers; it tends to preserve spatial information .

One step of the algorithm considers a vertical slice of the image, where the height represents the pixel value. One line thus produces a two dimensional graph, in which pixels in the umbra (ie below the image curve) are set to 1, and the rest to 0. Essentially, in one step of the convex hull, a pixel value is changed from 0 to 1 only if at least four neighbouring and contiguous pixels (out of eight neighbours) are 1.

The algorithm was compared advantageously with multi-looking and median filtering on synthetic SAR imagery. It is used at ERIM both for image presentation as well as preconditioning for further computer algorithms (Crimmins 1986).

4. SUMMARY

Speckle smoothing techniques can be categorised in different ways. They include:

(a) general methods such as linear filters, primarily applied to additive noise;

(b) homomorphic techniques, in which a multiplicative degradation can be converted into an additive one, allowing the application of the general techniques;

(c) non-linear filters such as the somewhat heuristic median and Sigma probability filters, based on a window around the pixel of interest;

(d) the well-established multi-looking techniques;

(e) image domain filters, in which the image is transformed in some way, a linear filter applied, followed by transformation back to the image domain;

(f) adaptive techniques based on the image statistics in a window around the pixel of interest;

(g) Bayesian techniques, based on known or assumed prior knowledge about the original image and noise statistics; and

(h) the geometric filter.

The standard noise model takes into account multiplicative noise only, although the refinement of including the point spread function has been made in the Kansas filter. Prior knowledge in the form of known or assumed original image and noise statistics has been included in some approaches. Most of the techniques discussed operate on the processed image; however multi-looking techniques are incorporated in the GSAR package.

A speckle size or texture can be observed on processed images. Some recent work has considered speckle smoothing, taking advantage of this spatial correlation (Kuan et al 1987). Such an approach may well tend to be computation intensive but represents one direction of future work.

The multiplicative nature and magnitude of speckle noise remains a significant problem both for visual interpretation of images and their classification.

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This survey reviews noise reduction techniques of particular relevance to the multiplicative speckle noise associated with synthetic aperture radar images. Where appropriate, mention is made of the Generalised Synthetic Aperture Radar (GSAR) software package developed by MacDonald Dettwiler and Associates for the processing of raw SAR data in a standard format into image data.

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